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Firms introducing network technologies (whose benefits depend on who installs the technology) need to understand which user characteristics confer the greatest network benefits on other potential adopters. To examine which adopter characteristics matter, I use the introduction of a video-messaging technology in an investment bank. I use data on its 2,118 employees, their adoption decisions and their 2.4 million subsequent calls. The video-messaging technology can also be used to watch TV. Exogenous shocks to the benefits of watching TV are used to identify the causal (network) externality of one individual user's adoption on others' adoption decisions. I allow this network externality to vary in size with a variety of measures of informal and formal influence. I find that adoption by either managers or workers in "boundary spanner" positions has a large impact on the adoption decisions of employees who wish to communicate with them. Adoption by ordinary workers has a negligible impact. This suggests that firms should target those who derive their informal influence from occupying key boundary-spanning positions in communication networks, in addition to those with sources of formal influence, when launching a new network technology.

Key words: Networks, Network Externalities, Technology Management

History:

1. Introduction

Firms and consumers benefit from the diffusion rather than the creation of new technologies (Rogers (2003)). Managing a technology's diffusion is particularly challenging for technologies that become more useful as more people adopt: Nobody wants to buy a telephone or video-conferencing unit if there is no-one else in the network to communicate with. If welfare-enhancing technologies cannot overcome this hurdle of attracting initial adopters, this inhibits the potential economic growth the new technology can bring.

This potential for sub-optimal diffusion, first documented by Rohlfs (1974), has been formalized into a theory of network externalities by economists such as Katz and Shapiro (1985) and Farrell and

Saloner (1985). To validate this theoretical work, empirical researchers have sought to document "network externalities". Network externalities measure how much adoption decisions reflect who else is in the network. If people adopt at the same time, however, it is difficult to know whether this adoption was a product of network externalities or of something else.

One way of addressing this empirical challenge is to compare how adopters react to similar regional networks that have different levels of adoption. However, this allows only the measurement of an average network externality in response to an average level of adoption. It does not measure individual responses to individual adoption decisions. Therefore, the network externalities literature has not been able to fully incorporate a wide body of managerial research that highlights how some key adopters can have a large influence on an individual's adoption process through a variety of social mechanisms.

To explore how network externalities vary at the individual level, I use video-messaging data that tracks the adoption of 2,118 employees in a large bank and their 2.4 million subsequent calls. The technology diffusion process somewhat resembled a large-scale experiment, because adoption decisions were decentralized to employees. The advantage of studying this particular video-messaging technology is that it has a stand-alone use of TV-watching that can be used to identify network externalities. This ability to watch TV varies in usefulness by location and time. Some employees were prompted to adopt the technology by TV programming such as the 2002 Soccer World Cup.

I measure the effect that this TV-inspired adoption has on other people's adoption decisions. I interpret this effect as showing the benefits that they receive from having that person in the network to communicate with. Since employees' communication networks differ, I can measure this network externality at an individual level. For example, I can compare the adoption decisions of two employees in the US, one who has many contacts based in countries where the Soccer World Cup was popular, and another who does not. These individual-level data allow me to explore how network externalities vary with any one adopter's potential influence. For example, I can explore whether a manager or a worker's TV-inspired adoption has a bigger effect on others' decisions to adopt. Using this to identify a network externality requires there to be no systematic reason why an employee who has a high proportion of contacts in a region that is having a TV-watching spurt should be more likely to adopt than an employee who has contacts in a region where there is no TV-watching spurt.

The ability to measure how network externalities relate to network users' characteristics allows me to explore whether network externalities reflect the potential for subsequent video-messages to differ in importance. Rogers (2003) describes two kinds of important conversations: Interactions with those who are higher up in a formal social structure, and interactions with those who occupy key positions in the informal communications structure. I explore what happens to the size of network externalities when we adjust for whether an adopter is important by either of these measures. I test a variety of measures of a user's importance within a communications network. I find that adopters who are high up in the formal hierarchy, or who occupy a boundary-spanning position between groups of uncommunicative employees in the informal communications network, have bigger network externalities on the adoption decisions of others. I also find evidence that those who occupy central positions in the communications network have a bigger network externality than those who occupy peripheral positions.

These findings emphasize that the successful introduction of a technology characterized by network externalities, depends on both people with formal influence and people with informal influence adopting the technology. Therefore, it is crucial when introducing new technologies to ensure that boundary spanners and those who are central to the firm's communication network are targeted to adopt quickly, in addition to those with formal sources of influence.

2. Network Externalities: Sociological and Economic Perspectives

This paper draws from both the economics literature on network externalities and the managerial literature on network effects. These two literatures have developed largely in isolation from each other.

Managerial and sociological researchers use the term "network effects" to refer to many processes through which someone's adoption can be influenced by another. Within the class of network effect models, two broad models can be distinguished (Burt (1987)). The first is the "contagion by cohesion" model, where adoption is based on direct contact. The second model is a "structural equivalence" model, where two people adopt the technology because they face a similar set of norms. The term "network externalities" in this literature is restricted to interactive technologies that offer a direct performance benefit from having more users. Network externalities are thought of as a special case of contagion by cohesion (Bulte and Lilien (2007)).

Since work by Burt (1980) and Friedkin (1991), this managerial literature on diffusion has documented in many different settings that adoption by key actors is associated with a larger number of subsequent adoptions. Typical of this work is Podolny and Stuart (1995)'s study of how niche technologies develop based on the patent holders' status. There has also been a stream of research that documents how social influence can lead to technology adoption bandwagons (Strang and Macy (2001), Abrahamson and Rosenkopf (1993)). Early research in marketing by Czepiel (1974) documented similar effects for word of mouth in the steel industry and studied how high centrality affected how quickly potential adopters found out information. This emphasis on heterogeneity of social processes is also echoed in a broader communications literature, described by Monge and Contractor (2003). I use this insight, that highly central actors can affect social learning, cascades and informational spill-overs, and test whether the same applies to the case of network externalities. Generally, network externalities have received less specific attention in this sociological literature because network externalities are a mechanical property of the technology (it mechanically becomes more useful as more people have it) rather than necessarily reflecting an underlying social process.

While sociologists use the term "network effects" to encompass a wide number of social processes, economists use "network effects" as a conservative way of describing what sociologists would call "network externalities". This reflects caution by economists about assuming a coordination failure, or "externality", before there is evidence that one exists. For example, in this paper, while it seems plausible that TV-inspired adopters do not internalize the benefits that their adoption brings to others, I present no direct proof that this is so. Furthermore, using the term "network externality" implies that the network owner does not internalize the benefits of widespread adoption in their pricing or incentive strategy, which is rare (Liebowitz and Margolis (1994)). In this paper, I use the less conservative term "network externalities" in order to be accessible to non-economists. The focus of empirical work in the economics literature has been to measure these "network effects" (externalities), and to distinguish the benefit that people receive from widespread adoption from the broader set of influences which might cause similar people to adopt. This focus on establishing a convincing identification strategy for network externalities stems from research by skeptics such as Liebowitz and Margolis (1994) who doubt the prevalence of network externalities. In the face of this skepticism that a coordination failure can persist in a systematic manner, empirical researchers have focused on finding convincing ways of identifying causal network externalities that cannot plausibly be ascribed to measurement error.

Early economics work on measuring network externalities used standard panel data techniques. These control for static differences in agents and also for a universal time trend. For example, Saloner and Shepard (1994) used region and time dummies when studying correlations in adoption of ATM networks by banks. Such empirical work, however, makes the strong assumption that there are no network-specific time shocks, such as a regional sales effort by ATM vendors, that could provide an alternative explanation of correlation in adoption decisions. Similarly, when studying the spreadsheet market for computers, Gandal (1994) and Brynjolfsson and Kemerer (1996) use time dummies to control for broad time trends, but cannot distinguish network externalities from product-specific shocks, such as an unmeasured increase in promotional activity. This criticism also applies to researchers using panel data outside of economics. For example, Kraut et al. (1998) studied network externalities for a video-phone system similar to the one studied in this paper. They controlled for time-specific shocks but did not control for unobservable differences across work groups over time that could be mistakenly interpreted as network externalities, such as a slowdown in demand where all employees in the work group had spare time to adopt.

The problems of using standard panel data methods to identify network externalities have led researchers such as Rysman (2004), Gowrisankaran and Stavins (2004) and Tucker (2004) to use instrumental variables to identify network externalities. They use a regional network-specific shock, such as adoption by a multi-region bank, as a source of exogenous variation for existing levels of adoption. Then, they measure how potential adopters respond to these exogenous changes in regional adoption. This approach has two limitations. First, it is difficult at the aggregate regional level to identify shocks that are unrelated to the characteristics of firms that are located there. For example, Gowrisankaran and Stavins (2004) assume that entry by a multi-region bank is unrelated to unobserved changes in technology tastes. Second, studying network externalities at this aggregated regional level does not allow study of how highly central actors affect diffusion. Instead, Gowrisankaran and Stavins (2004) take adoption by central actors such as multi-region banks as an exogenous shock that can be used to identify the reactions of smaller actors.

This difficulty in establishing causation at the individual level is widespread in many marketing and managerial problems, not just for network externalities. For example, in the case of switching costs, it is difficult to disentangle an individual's level of lock-in from their idiosyncratic preferences for a good (see Goldfarb (2006)'s study on consumer choices for internet portals). Therefore, one aim of this paper is to describe how individual data can be used to establish causation in a way that could be used to explore individual heterogeneity for these other managerial questions.

The contribution of my research is that I identify for the first time network externalities at the individual level, without strong assumptions about strategic behavior or an aggregate functional form of the network externality. The fact that the technology I study has a separate stand-alone use of TV-watching which is subject to a series of exogenous shocks makes it unusually possible to identify network externalities, despite the similarity of users' network use. What is unique about the identification strategy in this paper is that the exogenous variation comes at the level of the individual's network rather than the aggregate network. I use this individual data in two ways. First, I use exogenous variation in individual adoption incentives to identify the impact of adoption by one agent on related agents. Second, data at the individual level allow me to identify the differential impact of adoption by different types of adopters. In particular. I explore whether the many managerial insights into how highly central actors affect diffusion also apply to network externalities. It also reflects a nascent literature in economics, such as Sundararajan (2004)'s theoretical model of heterogeneity in network consumption.

The structure of this paper is as follows: Section 3 describes the video-messaging technology and the data and Section 4 sets up the empirical approach. Section 5 discusses the TV-watching identification strategy. Section 6 discuss the results and managerial implications. Section 7 discusses an important extension to the main results, where I use a predicted version of the underlying video-messaging networks to study the behavior of employees who do not adopt.

3. Technology and Data

3.1. Technology

Installing video-messaging can improve the effectiveness of internal firm communication, by adding visual cues to the audio cues provided by telephones. Marlow (1992) describes the benefits of video-messaging as greater intimacy, geographic reach, flexibility and effectiveness in communications.

Many older video-messaging systems were not popular because they were placed in isolated video-conferencing rooms. This research studies a more convenient form of video-messaging placed on desktop computers. The technology has three elements: Video-messaging software; a media compressor attached to the employee's computer; and a camera fixed on top of the computer's monitor. Using the language of Farrell and Saloner (1985), the video-messaging technology has a "network use" and a "stand-alone use." The network use is television-quality video-messaging calls. The stand-alone use is watching TV on a desktop computer.

After this bank chose this particular technological standard to conduct internal video-messaging, it invested in an extensive network architecture. The firm made employees eligible to adopt the technology if they held a position of Associate or higher (85% of full time employees). The firm publicized the technology to employees using mass e-mail messages. Then, for institutional and business reasons, they decided to decentralize individual adoption decisions to employees. Each employee decided whether and when to order a video-messaging unit from an external sales representative. The supplier of the equipment had excess capacity, so capacity constraints did not affect the timing of individual employee adoption. This decentralization means that the unit of analysis is the private benefits of adoption for employees, as opposed to the firm-level benefits of widespread adoption.

The bank incurred all monetary costs of using the technology. Though the employee did not pay for the technology, they did suffer a temporary loss of productivity from not being able to use their computer while the technology was being installed, and they also had to spend time learning how to use it. Talking to employees at the bank, the risk of prolonged computer "downtime" was viewed as the most substantial cost. In particular, fears were expressed about not having access to or being able to act upon constantly changing financial market data. Therefore, each employee had to set their perceived network and stand-alone use against their non-monetary costs of adopting.

The video-messaging technology is used only for internal communication within the firm. Having data on the universe of network interactions makes such closed-loop technologies attractive for empirical research.

3.2. Data

3.2.1. Personnel Database I have complete personnel records for each employee in the investment bank in March 2004. Employees were associated with two main products: Equities and derivatives. There were four broad different functions: Administration, Research, Trading and Sales. There is also information on the precise city location of each employee. I classify these locations into four broad regions: Britain, North America, Europe and Asia/Sub-Equatorial. There were four formal rungs in the hierarchy for employees at the firm. I combine the bottom two rungs "Associate" and "Vice-President" into the category "Workers", and the top two rungs "Director" and "Managing Director" into the category "Managers." 25.8% of employees were Managers.

A call database recorded the 2.4 million video-messaging calls made within the bank from January 2001 to August 2004. For two-way video-messaging calls, the database records the caller and callee, when the call was made and how long it lasted. For one-way TV calls, the database records who made the call, to which TV channel, when and for how long.

Employees made 1,768,348 two-way user-to-user video-messaging calls. The dataset includes only the 1,052,110 video-messaging calls where the callee accepted the call. Each accepted call lasted on average 5 minutes and 46 seconds. Calls could be made to more than one employee at a time. Multi-party calls (less than 5 percent of calls) were simplified into their pairwise equivalents: A three-way call is treated as three calls between each two of the participants. I use the first 2.5 years of the call data (from Jan 2001-Jul 2003) to examine calling decisions, and the last year of the call data (from Aug 2003-Aug 2004) to reconstruct the communications network within the firm.

Employees made 752,055 one-way caller-to-media-device calls. 741,926 of these calls were successful and included in the data. Since I want to control for regional-specific time trends, I focus on the use of the video-messaging technology for watching regional television broadcasts. Employees could also watch CNN and CNBC, but there is little cross-national variation in the proportion of employees watching these channels. Local channels for Europe were ZDF (German), ARD (German), Kanal (Swedish), ORF (Austria) and Eurosport. Local channels for Britain were ITV, SkySports, Channel 4 and BBC. Local channels for the US were CSPAN, FOX, NBC and CBS. Local channels for Asia were NTV (Nippon TV), CATS (Japanese), TV-Asia, and BBC 24 World Service.

4. Empirical Approach

I want to examine how adoption by different types of employees affects when and whether another employee adopts video-messaging. To do this I employ a latent variable approach, where I model each employee's adoption as a reflection of the trade-off they face between the network and standalone benefits and costs of adopting the technology. The dependent variable is an indicator for when an employee first makes a video-messaging call. Since there is no divestiture, I treat this adoption decision as irreversible and exclude subsequent observations in estimation.

4.1. Network Externalities: Network Benefits of Adoption

Employees receive network benefits from using this technology because they can communicate with colleagues using video rather than telephones. In addition to the benefits of being able to see each other when talking, the video-messaging technology offers auto-dial and "frequent contacts" lists. These features offer convenience relative to the existing telephone network. These network benefits explicitly depend on having other people also in the network. This paper makes the simplifying assumption that all employees take other employees' adoption decisions as given, and do not look forward to the impact that their adoption can have on others in the future. In Ryan and Tucker (2007), I explore the implications for the dynamics of the network when this assumption is relaxed.

I assume that network externalities depend only on the subset of adopting employees that employee i interacts with. This is supported by results in Table EC.10 and Tucker (2007), which show that network externalities are limited to direct contacts. I define employees as "contacts" if they video-message when both employees have adopted. I use data on whether employees shared a video-messaging call from August 2003-August 2004 to establish who each adopter's contacts are. These last 12 months form a reliably stable communications network: only 90 new adoptions occurred during this year, relative to the 1,294 in the previous 2.5 years. Given this stability, the precise choice of the months August 2003-August 2004 as a representative network does not affect contact predictions. Using a shorter snapshot such as (March 2003-June 2003) and (March 2003-December 2004) changes the composition of contacts for adopters by less than 5 percent.

It is important to be clear that my use of video-messaging data to establish contacts means that any network I recover is explicitly a network for video-messaging, that can be used to measure the size of network benefits/externalities for video-messaging conversations. It need not be representative of the social network in the firm as a whole.

These call data identify contacts for the 1,294 adopters, not for the 824 non-adopters. Initially I present empirical results for the influence of network externalities on the adoption timing of adopters. In section 7, I incorporate decisions by non-adopters by using the call data to predict their contacts. These later estimates capture the influence of network externalities on whether employees ever adopt, as well as how quickly they adopt.

The baseline measure of the "installed base" for an employee is the number of their contacts who have adopted the technology up to and including that month.[1]

[1] As I study direct network externalities, the installed base in my study is the subset of adoption decisions that matter to a potential adopter. This is different from the widespread use of the term "installed base" to refer to the universe of downstream adopters from the perspective of an upstream vendor when there are indirect network externalities. See Goldfarb (2006).

However, given my focus on how heterogeneity of network user characteristics affects adoption, I weight this basic measure to vary in magnitude depending on the characteristics of each contact.

4.2. Introducing Heterogeneity into the Contact Network

In my empirical analysis, I use six different measures of contact heterogeneity and weight the relative importance of each contact's adoption. These measures are intended to cover a wide spectrum of the social mechanisms affecting diffusion that are documented in the sociological literature (Burt (2000)). I first consider managerial status as a way that formal social structure may change the size of network externalities. Theories of hierarchy suggest that conversations with managers may be more crucial, so there may be larger network externalities for others when a manager adopts.

In addition to formal hierarchical status, it seems likely that conversations may vary in importance and consequently network externalities may vary in size if a contact has a higher amount of informal influence in the underlying communications network. To reflect informal influence, I use measures developed for social network analysis. These measures of "network centrality", or the importance of a contact in the underlying communications network topology, are described in detail in Table 1. I study three older measures of centrality: closeness, degrees and betweenness (Freeman (1977) and Granovetter (1973)), and also the more recent "Bonacich Power". Like Google's PageRank system for hyperlinks, Bonacich Power weights a contact's importance by how important their contacts are (Bonacich (1987)).[2] A technical description of how each of the measures is calculated is available in the online appendix (Table EC.5) . Finally, I include a measure of geographic distance between two contacts to measure whether video-messaging conversations, and consequently network externalities, become more valuable for geographically distant contacts.

Table 1 describes how different types of influence may affect the size of network externalities. Though these types of influence have been found to be important for other social influence mechanisms, it is not clear that they will hold for network externalities. For example, it is not clear that adoption by an employee with many other contacts will be more valuable than adoption by an

[2] Calculated using an attenuation factor of β=1 implying an increase in importance with contact's importance.

Table 1 Different Types of Heterogeneity

Influence Measure	Description	Possible effect on how important it is to video-message with contact
Measure of Formal Influence		
Managerial Status	Whether a contact is a manager (Director or higher)	Conversations with managers are more important
Measure of Informal Influence		
Betweenness	How many times a contact lies on the shortest network path between two other employees	Conversations with boundary spanners are more valuable as they have unique access to information
Closeness	The average length of the shortest path between the contact and all other employees	Conversations with central employees have more value than conversations with employees on periphery of firm
Degrees	How many contacts a contact has	Conversations with employees who have more conversations are more valuable because they contain more information
Bonacich Power	How powerful the contact's network is	Conversations with employees who have more conversations with other different employees who have more conversations are valuable because they contain more information
Distance	Distance in km between the employee's city and the contact's city	Conversations with video-messaging are valuable for contacts who are located far away, as it prevents tedious air travel

employee with few contacts. Having many contacts could indicate that the employee communicates multiple streams of trivial information, meaning that the value of video-messaging conversations with that employee would be lower.

I calculate these measures of centrality for each employee who adopted using software developed by Borgatti et al. (2002). All the measures of informal status use different units. Therefore, in my empirical specifications, I use a mean centered and standardized index of each of these measures, to ease comparison between their relative effect on the size of network externalities. The distribution of these standardized measures is displayed in Figure 1.

4.3. Controls

It is likely that the net costs of adopting the technology vary considerably across employees. For example, it may be easier for employees in more flexible areas, such as research, to schedule time for their computers to be down, than for employees who work in fast-paced areas such as derivatives trading. Therefore, I include a series of controls for each of the different functions and product

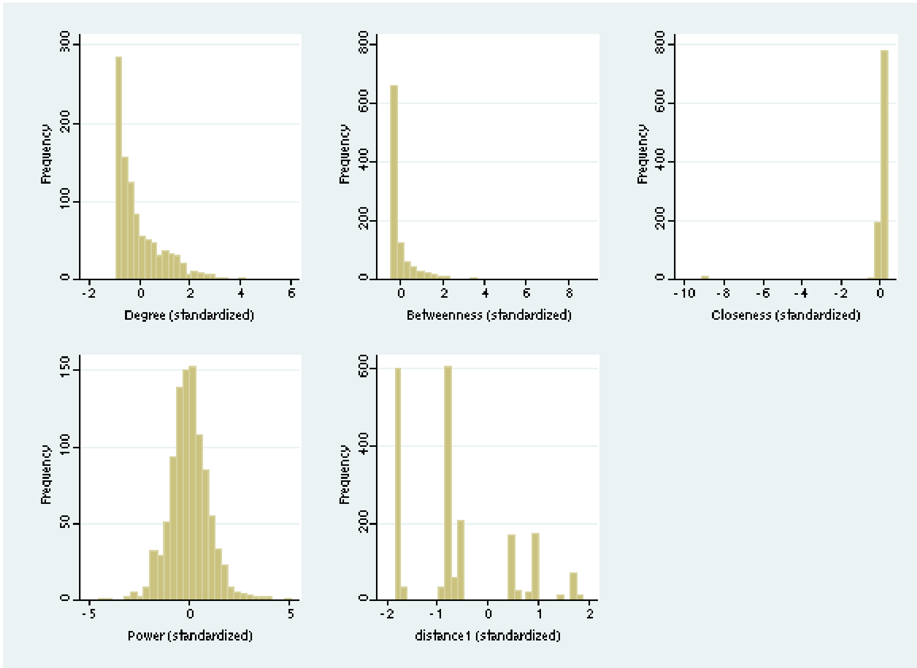


Figure 1 **Distribution of Centrality Measures**

groups. Similarly, there may be cross-national differences in technological competence and expected learning costs. To capture this I also include controls for each region. It is also likely that the net costs of adopting vary across time. Therefore, I include a series of dummies for each month that employees could potentially adopt the technology. Since these time dummies will also pick up selection and the changing baseline hazard rate, they cannot be interpreted.

This technology also had specific benefits that were independent of any network usage. In particular, employees enjoyed being able to watch television on their desktop computer. There were two types of television employees could watch: News TV programming on CNN and CNBC, which covers financial news; and local TV programming (often non-news) broadcast by country-specific channels. While there was little variation across regions in the percentage of adopters watching news programming, there was large variation in employee interest in local TV programming across regions. For example, employees in UK watched the 2002 Soccer World Cup, while employees in the US did not. Empirically, these local broadcast events were correlated with adoption in the month prior to the month they occur. This suggests that employees adopted the technology in advance to ensure they could watch predictable "must-see" television. I capture these regional shocks to the technology's stand-alone benefit by the variable TV_{rt} which contains the percentage of previous adopters watching "Local TV" in region r in the month following time t.

The video-messaging unit's TV use led to a less systematic pattern of adoption than is common for communication technologies. Table EC.3 shows that there is no monotonic relationship between adoption timing and the post-adoption intensity of usage of the technology. It is striking that those who adopted in May 2002 just prior to the World Cup make an average of only 8 calls a month, compared to the all-employee average of 17 calls a month. I use this regional variation in the stand-alone benefit to help identify a causal network externality.

5. Identification of Network Externalities

A network externality occurs when one employee adopts because they wish to video-message with another employee who has already adopted. The challenge is to quantify this. A correlation in the timing of two contacts' adoption does not conclusively demonstrate a network externality. This coincident timing could happen for many other reasons. For example, their boss could instruct two contacts to adopt a technology at the same time, or they could receive two contemporaneous calls from a sales rep. This endogeneity of adoption decisions resembles Manski (1993)'s distinction between contextual/correlated effects and endogenous effects in the social interactions literature.

One way of estimating a true network externality, therefore, would be if there had been a field experiment where a few employees were randomly selected to adopt. This randomness would mean that I could subsequently study the subsequent adoption decisions of two other employees who were otherwise identical, except that one of them had a contact who had been randomly commanded to adopt. Such intentional randomization is not present. However, in the data there is a lot of quasi-random adoption that is prompted by variation in the value of watching TV across months and across regions. Therefore, I use this variation as a natural experiment to approximate a true randomized trial. In particular, I exploit the fact the installed base of two employees in the same work group and location will receive different shocks, because they have contacts who value watching TV differently because they live in different regions. On average, fewer than 20% of employees in a work group had an identical regional composition of contacts.

I use instrumental variables to reflect this quasi-random adoption. I instrument for each month the heterogeneity-weighted measure of employee i's installed base using the heterogeneity-weighted average TV benefit for each of their contacts j. A contact's TV-watching benefit for that month is the proportion of previous adopters watching local TV in that contact's region in the next month. For each month and for each employee, I calculate the average TV benefit of each employee i's worker and manager contacts j $1/n \sum_j^n TV_{jrt}$. When I incorporate heterogeneity in informal influence into measures of the installed base, I weight the instrument accordingly.

The Soccer World Cup in June 2002 illustrates the identification strategy. Figure 2 shows how the percentage of this bank's employees who watch local TV programming varied across the US and UK in 2002. While the Soccer World Cup in June 2002 elicited great interest from employees in the UK, it did not interest many employees in the US. The World Cup is associated with a spike in adoptions in the UK in May 2002. There is no May spike in the US - but there is a smaller spike in June. Figure 3 shows that the spike in adoptions in the US in June 2002 is dominated by employees in the US reacting to the TV-inspired adoption of the technology by their contacts in the UK. This anecdote illustrates the identification strategy. I do not count all earlier adoption by i's contacts as necessarily causing i's adoption. Instead, I use variation in employee i's contacts' adoption that can be predicted by variation in the stand-alone (TV) benefit. For this to identify a causal network externality requires that there be no systematic reason why an employee who has a high proportion of contacts in a region that is having a TV-watching spurt should be more likely to adopt than an employee who does not have contacts in that region.

Figure 2 Relationship between new adoptions and TV-watching in the US and UK, 2002

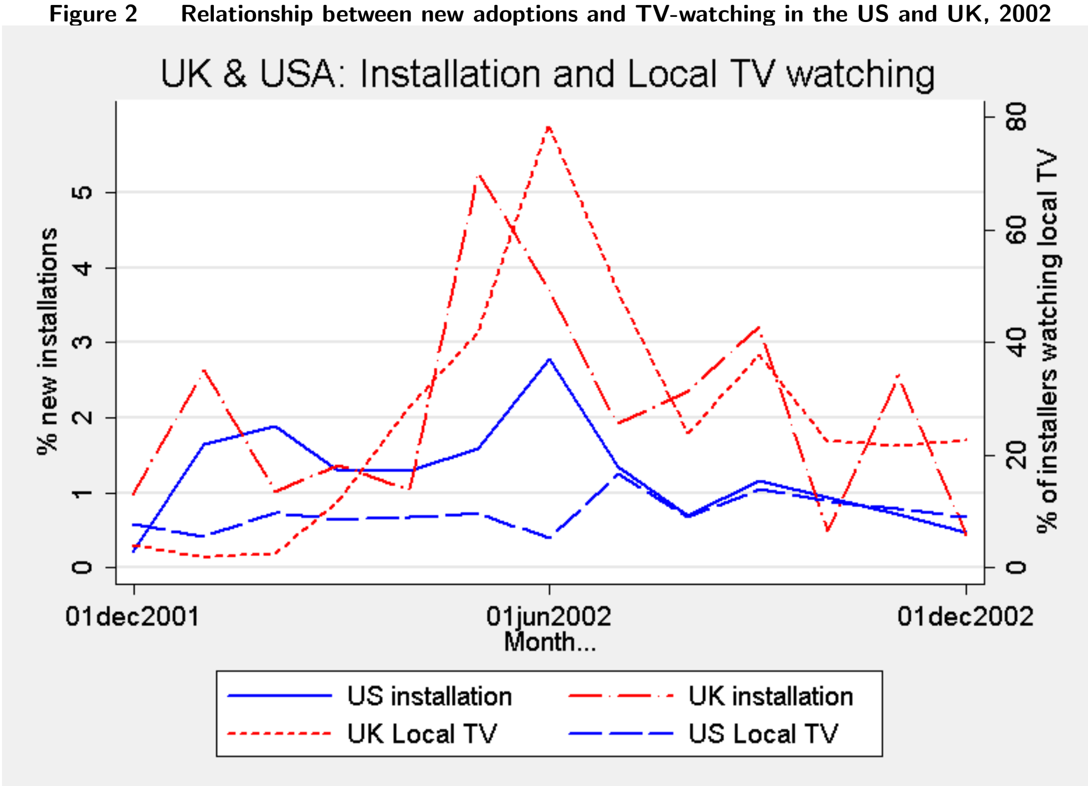
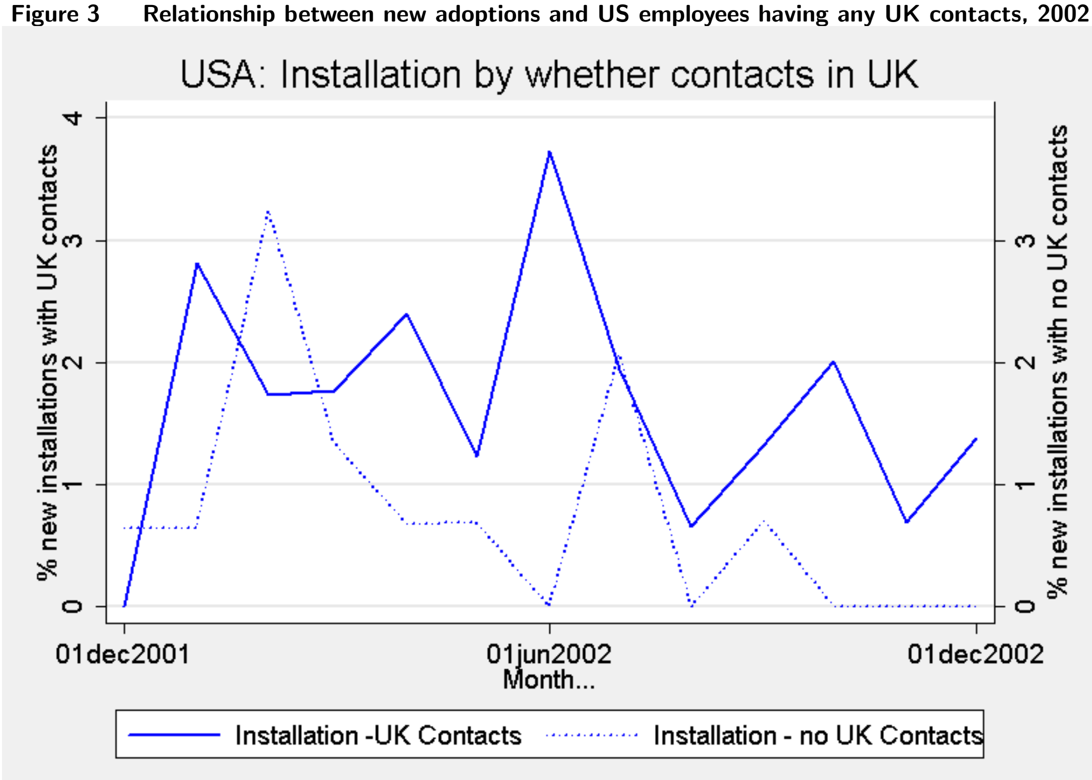


Figure 3 Relationship between new adoptions and US employees having any UK contacts, 2002



6. Estimation and Results

As discussed by Allison (1982), discrete-time hazard models can be estimated using standard binary discrete choice models such as a binary probit, if all the data are organized into a panel and all post-adoption observations are deleted. Since empirical methods for dealing with endogeneity are more advanced for discrete choice models than hazard models, I follow a discrete choice specification. I estimated each employee's response to the installed base using Newey's two-step minimum chi-squared estimator for probit with endogenous regressors (Newey (1987), eq. 5.6). My specification includes instrumented measures of the installed base for each adopter, control variables for the TV benefit in the potential adopter's region, and dummy variables for product, region, function, title and every month. Table 2 displays summary statistics for each of the main regression variables.

To illustrate my identification strategy, I first present results from a simple regression where I measure separately how a potential adopter responds to adoption by manager and worker contacts. This allows a simple measure of whether formal position in the hierarchy matters for the size of network externalities. I stratify my estimation by whether the potential adopter is a manager or worker. The estimates are reported in Table 3. A rough calculation of marginal effects at the mean value suggest that adoption by a manager contact increases the probability of a manager adopting by 0.02, up from a baseline probability of adoption of 0.10 in each month. Adoption by a worker contact has a negligible effect on a manager's adoption decision. Adoption by a manager contact increases the probability of a worker adopting by 0.007, up from a baseline of 0.05 in each month. Adoption by a worker contact has a far smaller marginal effect on other workers' adoption decisions, of 0.002. Therefore, an increase in the installed base of managers for employee i has a larger effect on i's adoption decision than an increase in the installed base of workers.

The influence of television, as measured by the percentage of previous adopters watching television in that region, is positive and significant. The estimates for the "pull" of television were greater for workers rather than managers. This implies more generally that when firms introduce network technologies, they should focus on a compelling stand-alone use to ease initial adoption.

Table 2 Description of all variables used in regressions

Variable	Description	Mean	Std. Dev.
	Dependent Variables		
$FirstAdoption_{it}$	Indicator Variable for first month a worker makes outward video-messaging call	0.05	0.244
$FirstAdoption_{it}$	Indicator Variable for first month a manager makes outward video-messaging call	0.10	0.284
	RHS Variables		
Variable	**Description**	**Mean**	**Std. Dev.**
$InstalledManager_{it}$	Sum of cumulative adoption by employee i's contacts who have a title of Director or higher by month t	1.309	1.641
$InstalledManager_{it}$ (Bet)	$InstalledManager_{it}$ weighted to reflect each manager contact's standardized betweenness score	1.486	2.782
$InstalledManager_{it}$ (Closeness)	$InstalledManager_{it}$ weighted to reflect each manager contact's standardized closeness score	0.263	0.485
$InstalledManager_{it}$ (Degrees)	$InstalledManager_{it}$ weighted to reflect each manager contact's standardized number of degrees (contacts)	1.585	2.798
$InstalledManager_{it}$ (Power)	$InstalledManager_{it}$ weighted to reflect each manager contact's standardized power score	0.035	1.019
$InstalledManager_{it}$(Distance)	$InstalledManager_{it}$ weighted to reflect the standardized distance index between i and each manager contact	-0.311	1.271
$InstalledWorker_{it}$	Sum of cumulative adoption by employee i's contacts who have a title lower than Director by month t	7.684	8.705
$InstalledWorker_{it}$ (Bet)	$InstalledWorker_{it}$ weighted to reflect each worker contact's standardized betweenness score	9.313	11.818
$InstalledWorker_{it}$ (Closeness)	$InstalledWorker_{it}$ weighted to reflect each worker contact's standardized closeness score	1.569	1.993
$InstalledWorker_{it}$ (Degrees)	$InstalledWorker_{it}$ weighted to reflect each worker contact's standardized number of degrees	10.442	13.755
$InstalledWorker_{it}$ (Power)	$InstalledWorker_{it}$ weighted to reflect each worker contact's standardized power score	-0.094	1.644
$InstalledWorker_{it}$ (Distance)	$InstalledWorker_{it}$ weighted to reflect the standardized distance index between i and each worker contact	-2.271	5.769
TV_{rt}	Proportion of adopters in the employee's region r who have adopted prior to month t who watch local television channels in month $t+1$	0.336	0.359
Controls for Regions	Dummies for Europe, Asia, US and UK		
Controls for Month	Dummies for each month from February 2001 to August 2003		
Controls for Product	Dummies for equity and derivatives product group		
Controls for Function	Dummies for working in administration, research, trading and sales		
Total Observations	12723		

The instruments for the counts of the installed base are significant at the 1 percent level. The importance of the instrumental variables strategy is shown by comparing regular probit estimates (in the first column of Table 3) with the two-step results. The probit estimates are larger. This suggests that without the instrumentation strategy, correlated effects would wrongly be identified as network externalities. In some cases, this could inflate estimates of network externalities by 50 percent. Furthermore, the probit estimates are not identically larger across the different installed base measures, suggesting that unobserved heterogeneity differs systematically across different contacts. This makes a crude comparison of the relative magnitude problematic.

I augment these results using measures of formal hierarchical influence and the informal social

Table 3 Instrumentation Strategy

	Managers		Workers	
	Probit	**Probit IV**	**Probit**	**Probit IV**
[-2ex] Actual Installed Manager	0.1423***	0.0994***	0.0674***	0.0645**
	(0.0182)	(0.0261)	(0.0187)	(0.0251)
Actual Installed Worker	-0.0021	0.0030	0.0213***	0.0177***
	(0.0042)	(0.0054)	(0.0032)	(0.0038)
TV in employee's region	0.1808*	0.2008**	0.3438***	0.3790***
	(0.0927)	(0.0948)	(0.0745)	(0.0755)
Observations	4635	4635	8088	8088

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: Adopters who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the installed base are the average TV valuation of each employee's manager and worker contacts.

TV valuation is measured by the % of prior adopters who watch local TV in that contact's region in the next month.

* p<0.10, ** p<0.05, *** p<0.01

system implied by the communications data. This use of call data extends previous work such as Kraut et al. (1998) on video-messaging diffusion, that lacked such data to incorporate into their analysis. The results are displayed separately for workers and managers in Table 4. Each column reports results for a different specification, where I allow the installed base (and consequently the instrument) to be weighted by a different measure of a contact's informal influence. A rough calculation of the relative magnitudes of the marginal effects is provided in Table 5. These marginal effects should be interpreted as the effect on potential adopter i of adoption by employee j, when employee j is one standard deviation above the mean by that measure of informal influence. I discuss the relative impact of these measures of informal influence in turn.

"Betweenness" is, loosely, the number of times that the employee lies along the shortest path between two employees in the video-messaging network. Network externalities may increase in size with betweenness if conversations with contacts who occupy boundary-spanning positions in the video-messaging network prove more valuable. Adoption by a manager who has a betweenness level that is one standard deviation above the mean increases the likelihood of a manager adopting by an insignificant amount and of a worker adopting by 0.004. This is lower than the unweighted measure of network externalities for managers. This suggests that introducing betweenness for managers introduces measurement error, and that managers who are more "between" have no larger impact than those who are less between. Adoption by a worker who has a betweenness level that is one standard deviation above the mean increases the likelihood of a manager adopting by 0.001 and of a worker adopting by 0.002. This is larger than the unadjusted measure, in particular for potential adopters who are managers.

The fact that incorporating betweenness into measures of influence can turn measures of network externalities upside down is plausible. Previous work by managerial researchers emphasizes that betweenness can confer power outside of the hierarchy. Burt (1992)'s work on "structural holes" highlights how those who broker gaps in communication networks wield social capital. Outside the sociological literature, Hansen (1999)and Tushman (1977) discuss the importance of boundary spanners for knowledge and innovation sharing.

"Closeness" is a measure of how few stages it takes a contact to reach everyone else on the network. Visually, contacts who are in the center of a network are more likely to be "close" than contacts on the periphery. Network externalities may increase with closeness, if employees find it more valuable to talk with employees who are central rather than peripheral to the firm. However, it could also be that adoption by non-close employees will have larger network externalities on adoption by others, since video-messaging allows potential adopters to track down people who are hard to reach by other means. Adoption by a worker who has a closeness level that is one standard deviation above the mean increases the likelihood of a manager adopting by 0.007 and of a worker adopting by 0.008. Adoption by a manager who has a closeness level that is one standard deviation above the mean increases the likelihood of a worker adopting by 0.04 and of a manager adopting by 0.027. As Figure 1 shows, the distribution of this measure is highly skewed in a bi-modal manner, making any interpretation questionable. However, these results do provide some evidence that those who have above-average closeness also confer larger network externalities than the norm. This implies that network externalities are larger in general for employees who occupy central rather than peripheral positions in the firm.

"Degree" is a measure of how many contacts an employee's contact has. Network externalities may be larger for contacts that have many contacts because they have more access to information. Adoption by a worker who has a number of contacts that is one standard deviation above the mean increases the likelihood of both a worker and a manager adopting by 0.001. A comparison to the unweighted results suggests that having a large number of contacts leads workers to have a larger network externality on others than workers who have few contacts. However, adoption by a manager who has a number of contacts that is one standard deviation above the mean increases the likelihood of a worker adopting by 0.005 and has an insignificant impact on other managers. This suggests that, like with betweenness, the impact of a manager's adoption does not vary systematically with their number of contacts. In general, the results that incorporate degrees into the measure of network externalities resemble (at a smaller magnitude) those for betweenness. This is unsurprising, given that there is a 0.82 correlation between the two measures - having more contacts mechanically increases the likelihood of spanning boundaries between them. The fact that the estimates for the effect of betweenness are larger, however, makes it plausible that betweenness is the more crucial measure.

"Bonacich Power" is a measure of how important an employee's contacts' contacts are. Network externalities may increase with Bonacich Power if employees weight conversations with well-connected contacts more. Weighting the installed base by this measure led to a series of insignificant and negative point estimates, suggesting that in this case the mere fact of being connected to important people was not enough to lead a contact to have a large network externality on the adoption decision of others.

The distance weighting I use is simply a measure of whether network externalities increase with linear distance between two employees.[3] It might be reasonable to assume that I value a

[3] I obtain similar results when using non-parametric specifications that reflect whether workers and managers are on different continents.

conversation by video-messaging more if my contact is far away, because I benefit from not having to make an arduous business trip. I find, however, that this logic applies only to the adoption responses of managers to the adoption of far-flung manager contacts. By contrast, workers seem to receive larger network externalities from other workers who are closer to them. One interpretation of this result is that it is only conversations with managers that warrant actual travel and that managers, being older, prefer to avoid long-distance travel more than workers. Another possible interpretation is that employees in general do not value conversations with workers who are located a long way away from them, perhaps because they tend to be located in more peripheral offices such as in South-east Asia and Australia. Alternatively, video-conferencing may serve as a complement to face-to-face communication, rather than a substitute for these workers (this is discussed in the theoretical literature such as Gaspar and Glaeser (1998), Daft and Lengel (1986)).

6.1. Robustness

Generally, with panel data, we are concerned about controlling for the unobserved component in the error term. For example, researchers may wish to control for unobserved individual-level heterogeneity, such as systematic differences in technological aptitude. By contrast, in an experimental setting, the randomized nature of the treatment controls for such correlation across and within subjects. Similarly, if the exogenous shocks that underlie instrumental variables are randomly distributed, then they should also control for such serial correlation across and within subjects. This suggests that if instruments are valid, the instrumented endogenous variable is unrelated to unobserved components of the error term. However, it is common for researchers who combine panel data with instrumental variables also to provide robustness checks. This both checks for robustness and controls for any unobserved systematic relationship between shifts in instruments and individuals in the data. In this section, I discuss the various specifications that I have used to ensure the robustness of my results.

The Newey two-step estimator does not offer the same flexibility for specifying the error term as maximum likelihood. It is impossible, however, for two endogenous installed base measures

Table 4 Centrality Measures: Effect on Timing of Adoption

	Managers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0030	0.0077***	0.0366*	0.0057**	-0.0279	-0.0140**
	(0.0054)	(0.0028)	(0.0209)	(0.0028)	(0.0220)	(0.0065)
Installed Manager	0.0994***	0.0152	0.2134**	0.0143	-0.0263	0.0483*
	(0.0261)	(0.0109)	(0.0841)	(0.0129)	(0.0331)	(0.0281)
TV in employee's region	0.2008**	0.1959**	0.1762*	0.2079**	0.3302***	0.2740***
	(0.0948)	(0.0928)	(0.0937)	(0.0935)	(0.0881)	(0.0916)
Observations	4635	4635	4635	4635	4635	4635
	Workers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0177***	0.0123***	0.0712***	0.0092***	-0.0128	-0.0206***
	(0.0038)	(0.0030)	(0.0178)	(0.0025)	(0.0196)	(0.0060)
Installed Manager	0.0645**	0.0251*	0.3132***	0.0395***	-0.0284	0.0117
	(0.0251)	(0.0135)	(0.1138)	(0.0147)	(0.0345)	(0.0353)
TV in employee's region	0.3790***	0.3744***	0.3777***	0.3639***	0.4633***	0.3996***
	(0.0755)	(0.0746)	(0.0756)	(0.0760)	(0.0714)	(0.0726)
Observations	8088	8088	8088	8088	8088	8088

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: Adopters who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the heterogeneity-weighted installed base are the heterogeneity-weighted TV valuation of each employee's manager and worker contacts. TV valuation is measured by the % of prior adopters who watch local TV in that contact's region in the next month.

* p<0.10, ** p<0.05, *** p<0.01

Table 5 Marginal Effects

	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
			For Manager Adopters			
Installed Worker	X	0.001***	0.007**	0.001*	X	-0.0024*
Installed Manager	0.017***	X	0.027**	X	X	0.007*
			For Worker Adopters			
Installed Worker	0.002***	0.002***	0.008***	0.001***	X	-0.0024***
Installed Manager	0.007**	0.004*	0.040**	0.005**	X	X

Only significant estimates reported * p<0.10, ** p<0.05, *** p<0.01

to converge in a discrete framework under maximum likelihood. It is possible to use maximum likelihood for a linear probability model, and to estimate for this linear model robust/standard errors clustered by region. The results given in tables EC.6 and EC.7 retain statistical significance. Allowing for correlation within specialization, regions and functions produced qualitatively similar results. The irreversibility of the adoption decision prevents the estimation of individual fixed effects over time or other methods that econometricians commonly use to deal with serial correlation, since each observation is a series of zeros followed by a 1 (Chamberlain (1985)).

Following Allison (1982), I use a threshold model of technology diffusion rather than a hazard model. The month dummies substitute for the hazard model's flexible specification of baseline hazard heterogeneity. The results in Tables 3 and 4 are representative of a variety of possible month dummy and product/function/region interactions that I tried. This suggests that the current specification is able to control for selection and systematic differences in baseline adoption probabilities for those who adopt in 2003 compared to those who adopt in 2001. In particular, the similarity of the results, even allowing for differences in baseline hazards across different types, alleviates the concern that there may be systematic differences in the evolution of the baseline hazard rate for different types of employees that could contribute to measurement error.

I assume that an employee values adoption of video-messaging only by their contacts, rather than valuing an increase in the network size in general. This is discussed in detail in Tucker (2007), where I presents results showing that it is only the adoption decisions of others in the network to whom potential adopters are directly connected that are statistically significant for adoption decisions. Adoption by contacts to whom the employee is not directly linked does not have an effect on their adoption decisions which is significantly different from zero.

The instrumental variables procedure allows the interpretation that Tables 3 and 4 capture the reaction of a potential adopter to another's adoption decision. Causation is established by isolating the reaction of adopters to TV-inspired adoption decisions. It would be conventional in the case of a communications technology to interpret these as a straightforward physical network externality. An alternative interpretation is a "word-of-mouth" effect. This "word-of-mouth" effect could occur when employees adopt video-messaging in response to the adoption of their contacts because these contacts inform them of the merits of the technology. The empirical importance of word-of-mouth in the diffusion of new products has received increasing attention in the marketing literature (Godes and Mayzlin (2004)). Two factors, however, argue against a word-of-mouth interpretation in this case. First, there was no correlation in adoption in workplaces where one would expect a large word-of-mouth effect. Second, statistical analysis of people's reactions to those who used the technology predominantly to watch TV did not show a similar size of network externality as for those who used the technology to video-message.

7. Recreating the Communications Network

So far, all estimates have focused on how network externalities influence the adoption timing of the 1,294 employees who adopt the technology. However, this does not explore the equally interesting question of why 824 employees did not adopt. The challenge of including these decisions in the regressions is that we do not know whom the non-adopters would have video-messaged with if they had adopted. The identification strategy rests crucially on differences in the location of each employee's contacts. One alternative for establishing whom non-adopters may have video-messaged with is to use data from existing communication networks, such as e-mail records or telephone records, and assume that video-messaging would follow a similar pattern. For reasons of legal confidentiality, however, I have not been given access to such data. Therefore, I use the video-messaging behavior of adopters to predict whom non-adopters would have video-messaged with if they had adopted.

Since using adopter behavior to predict non-adopter behavior requires some strong assumptions, in this section I lay down the empirical steps that lead to this strong model of non-adopter behavior. In essence, I assume that the mathematical structure of the relationship between adopter characteristics and their contacts applies out of sample, to non-adopters. In other words, there are a set of Z features of users that generate a set of contacts, W. However, I observe this relationship W(Z) only when an employee adopts. I do not observe W(Z) when the threshold condition is not met and there is no adoption. Table 6 presents estimates for employee adoption as a function of Z. The probability of adoption is increasing in certain characteristics, in particular whether the adopter is European, in Admin, or a manager.

The number of contacts an employee has varies significantly with the employee's role in the firm. Table 6 also illustrates that the size of the contact list for adopters is increasing in the same

Table 6 Adoption and Contacts by Adopter Characteristic

	Percentage Non-Adopter	Percentage Adopter	Number of Contacts
		Region	
Asia	52	48	11
Europe	14	86	26
UK	17	83	21
US	45	55	17
		Function	
Admin	9	91	35
Research	38	62	17
Sales	27	73	18
Trading	41	59	18
		Title	
Associate	56	44	16
VP	36	64	18
Director	18	82	19
MD	8	92	28

characteristics as their propensity to adopt. For example, not only are European-based employees, Managing Directors and Administrators more likely to adopt, but they are also more likely to have more contacts. I cannot, on the basis of this evidence, conclude what the contact list would have looked like for non-adopters. However, if I assume both follow the same function, then any simulation of the post-adoption contact list for the non-adopters should show that the non-adopters have a lower number of simulated contacts. It is therefore reassuring that I predict a mean of 15 contacts for non-adopters and 22 contacts for adopters in my simulation of the network, with a standard error of prediction of (0.004). This is consistent with the basic predictions of the underlying network model. Under this strong assumption, that the nature of contacts can be predicted reliably on user characteristics, I can define a "strong model" where contacts are generated by the same underlying process for adopters and non-adopters. It is for this strong model that I present results on network externalities.

The actual procedure I use for simulating the network is more nuanced than suggested by Table 6. This is a sparse network. Out of 1.5 million potential links, there were only 23,805 actual links. To predict whom non-adopters would have called, I take the last 12 months' calling data as representative of communications in the firm, and use it to estimate communication choices. I regress an indicator variable for whether or not i video-messaged j or j video-messaged i on a vector of interaction dummies for each pair of caller i and callee j's characteristics. These interaction dummies include an indicator variable for every possible combination of caller city and callee city.

The interaction variable for a caller in New York and a callee in London captures the incremental effect on the probability of a link if the caller is based in New York and the callee is based in London. There are also interaction dummies for every possible combination of caller and callee title, product, product market, specialization and title in the firm (See Table EC.8 for a full description).

For each non-adopter i, I use the sum of these probabilities to predict the total number of contacts they would have called if everyone in the firm had adopted. I determine the predicted composition of their contacts by ranking the predicted likelihoods of employee i calling employee j. For adopters, I use a similar methodology to predict the unobserved part of their contact network.

To evaluate how well this procedure predicts contacts, I redid the above, using data for adopters from August 2001-August 2002 to predict contacts for those who adopted in August 2002-August 2003. The results suggested that contacts are predicted correctly approximately 60% of the time.

Table 7 gives the results for this full dataset that includes the decisions of non-adopters never to adopt. The results suggest that adoption decisions by managers have larger network externalities on the adoption of both workers and managers than adoption by workers. In this specification, adoption decisions by workers have a statistically insignificant effect for both managers and workers. The results that adjust network externality size by measures of centrality are slightly different from before. While the betweenness of a worker undoubtedly has a larger impact than closeness or degrees on the adoption decisions of workers, it no longer has a statistically significant impact on the adoption decisions of managers. It is also noticeable that weighting network externalities by centrality leads to a general lack of significance when measuring the impact of managers on both worker and manager adoption. Again, there are no statistically significant results from allowing network externalities to vary in size depending on Bonacich Power.

It is noticeable that the results for distance remain the most similar to before, with both managers and workers receiving positive network externalities from the adoption of workers who are close by and the adoption of managers who are far away. One explanation for the fact that these results more closely echo the previous results is that distance between non-adopting contacts can be measured precisely, whereas the centrality measures rely on an accurate prediction of the unseen video-messaging network.

In general, though, these results are reassuring that the previous results in Table 4, showing how heterogenous network externalities affect the timing of adoption by employees who do adopt, also apply to whether employees adopt. In both cases, network externalities are greater in size for managers and "between" workers than for regular workers.

7.1. Limitations

There are limitations in how widely these results can be applied. I am able to estimate precisely how adoption by other employees affects the timing of adoption for employees who ultimately adopt a particular technology in a single firm at a certain point of time. Since this is a communications technology, it is natural to interpret these adoption responses as a network externality, and I provide some limited evidence that suggests that they were not "word-of-mouth" effects. I extend these results to non-adopters to allow analysis of the adoption decision itself, though the trade-off in using predicted networks is less precision in estimation. It is also important to be clear that the network for which I estimate these network externalities is the one for video-messaging. This may not resemble the communications networks for other technologies.

8. Conclusion and Implications

This paper identifies network externalities at the individual level and then uses that identification strategy to evaluate how network externalities vary in size with well-recognized measures of formal and informal influence within the firm. My estimates show a great deal of heterogeneity in the size of network externalities that one individual confers on another's adoption decision. I am able to identify this individual heterogeneity by using a unique identification strategy. I use variation in how someone's contacts value the technology's stand-alone use of watching television as a quasi-experiment that leads to exogenous changes in a potential adopter's installed base. This allows me to identify an individual-level causal network externality, that is, how one person's adoption of a network good depends on who else is in the network to communicate with. This use of variation

Table 7 Predicted Network: Comparison of Different Centrality Measures

	Managers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0102	0.0101	0.0152***	0.0088***	0.0213	-0.0221***
	(0.0157)	(0.0150)	(0.0036)	(0.0023)	(0.0231)	(0.0059)
Installed Manager	0.0190***	-0.0401	-0.0244	-0.0121	0.0262	0.0899***
	(0.0041)	(0.0477)	(0.0200)	(0.0100)	(0.0408)	(0.0226)
TV in employee's region	0.3295***	0.4527***	0.3903***	0.3703***	0.4543***	0.4142***
	(0.0825)	(0.0869)	(0.0814)	(0.0817)	(0.0780)	(0.0803)
Observations	8186	8186	8186	8186	8186	8186
	Workers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0089	0.0586***	0.0124***	0.0102***	0.0290	-0.0241***
	(0.0220)	(0.0178)	(0.0027)	(0.0020)	(0.0197)	(0.0050)
Installed Manager	0.0272***	-0.0731	0.0034	-0.0024	-0.0026	0.0735***
	(0.0034)	(0.0963)	(0.0186)	(0.0125)	(0.0418)	(0.0269)
TV in employee's region	0.4979***	0.6690***	0.5057***	0.5324***	0.6017***	0.5503***
	(0.0614)	(0.0655)	(0.0617)	(0.0607)	(0.0586)	(0.0588)
Observations	23603	23603	23603	23603	23603	23603

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: All employees who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the heterogeneity-weighted installed base are the heterogeneity-weighted TV valuation of each employee's manager and worker contacts. TV valuation is the % of prior adopters who watch local TV in that contact's region in the next month.

* p<0.10, ** p<0.05, *** p<0.01

at the individual level sets this research apart from previous research on network externalities. Previous research has had to make strong assumptions about the randomness of timing of aggregate shocks to a network. In addition to a more robust identification strategy, this exogenous variation allows analysis of whether network externalities have a similar pattern of heterogeneity to other social processes affecting diffusion.

Generally, technology management policy towards encouraging diffusion of network technologies has followed the predictions of the theoretical literature on network externalities, and has focused on maximizing network size. My results suggest that this policy approach will not be optimal in all circumstances. A more appropriate policy, for similar technologies, would be to focus incentives at marginal influentials who are potential leaders of others' adoption, as opposed to the marginal user in general. My results also emphasize that it is not enough to target only those who occupy positions of formal authority. It is also important to target those who have influence because they occupy key positions spanning disparate communication networks or, potentially, those who are central to the communications network.

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Supporting Empirical Evidence

EC.1. Details about the Call Data

Table EC.1 illustrates how calls ended. In my empirical analysis, I exclude calls which were refused or where the call timed out. Table EC.2 illustrates the relative proportion of two-way video-messaging calls and one-way calls where video was broadcast in only one direction. The majority of these one-way calls were television broadcasts. These proportions suggest that the network usage of video-messaging dominated the stand-alone usage of TV, in terms of call volume.

Table EC.1 How the Call Ended by Call Duration

EndEvent	No Call Duration	Positive Call Duration	Total
Allocation Failed	66	0	66
Collapsed	781	30,518	31,299
Error	76,780	110,110	186,890
Forwarded	14,450	64,064	78,514
Hangup	180,229	1,532,876	1,713,105
Redirected	4,129	57,608	61,737
Refused	82,404	144	82,548
Ring Timeout	363,930	2,314	366,244
Total	722,769	1,797,634	2,520,403

All calls with no call duration, that are refused or where the ring times out are dropped from the data

Table EC.2 Number of Two-Way video-messaging Calls and One Way TV calls

Item	Number of Calls	Percent
One Way	752,055	30
Two Way	1,768,348	70
Total	2,520,403	100

EC.2. Details about the Personnel Data

The data do not indicate whether personnel details changed between January 2001 to August 2004. It is more likely that an employee got promoted than changed work group or city, given geographic immobility and group-specific human capital. Accordingly, an employee is described as a manager if she was on an upwards career trajectory which meant she would be a manager by 2004. The personnel records do not include data on employees who left the firm before 2004. Observations of these employees' calling patterns are excluded from the dataset.

The dataset excludes 127 personnel records of employees who joined the firm after January 2001: The unfavorable business climate from 2001-2003 means that the firm made few new appointments. The dataset also excludes 18 employees in Moscow, Bangkok and Athens, since the video-messaging infrastructure did not connect to these cities.

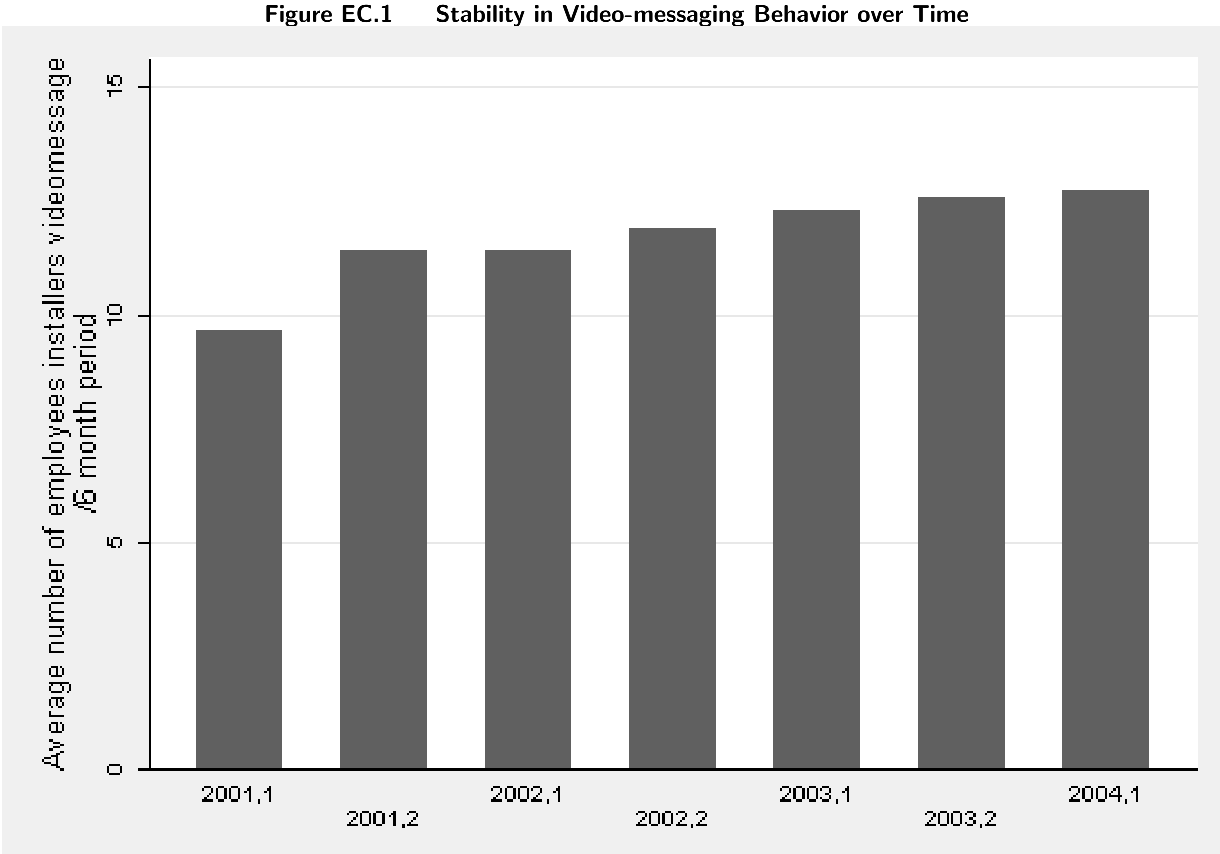
EC.3. Relationship Between Usage Intensity and Adoption

Table EC.3 illustrates the relationship between adoption in each month and the subsequent intensity of usage. It is clear there is no monotonic relationship between how early someone adopted and how much they ultimately used the technology. One interpretation is that this reflects the lack of video-messaging use by groups of early adopters who adopted the technology to watch television. The measure of what proportion of how many days each month an employee spent using the technology is somewhat distorted upwards by a few extreme values. A few Scandinavian employees left their video-message screen open for days on end. Figure EC.1 provides evidence that the number of different people that an adopter calls on average remains relatively stable over time. Figures EC.2 explores the relationship between the number of calls and the timing of adoption, and it is clear that again this is not monotonic. Figure EC.3 explores the relationship between the number of contacts and number of calls, and shows that in general employees who have more contacts are making more calls to these contacts.

Table EC.3 Relationship between Adoption timing and Usage intensity

Year-Month of Adoption	Average total calls in last 12 months	Average time spent video-messaging each month (one unit is one day
200102	287.11	1.03
200103	136.75	0.57
200104	101.89	0.40
200105	242.19	0.82
200106	168.32	0.88
200107	87.27	0.24
200108	194.78	0.60
200109	260.59	0.96
200110	144.32	0.44
200111	57.48	0.19
200112	114.93	0.30
200201	77.94	0.26
200202	113.09	0.33
200203	52.94	0.19
200204	277.73	0.86
200205	96.74	0.38
200206	197.17	0.95
200207	186.55	0.56
200208	118.59	0.49
200209	166.07	0.67
200210	273.86	1.88
200211	376.43	1.48
200212	167.14	2.44
200301	147.50	0.71
200302	91.00	0.32
200303	252.13	1.24
200304	158.70	0.55
200305	239.44	1.02
200306	96.00	0.52
200307	254.59	0.97

Figure EC.1 Stability in Video-messaging Behavior over Time



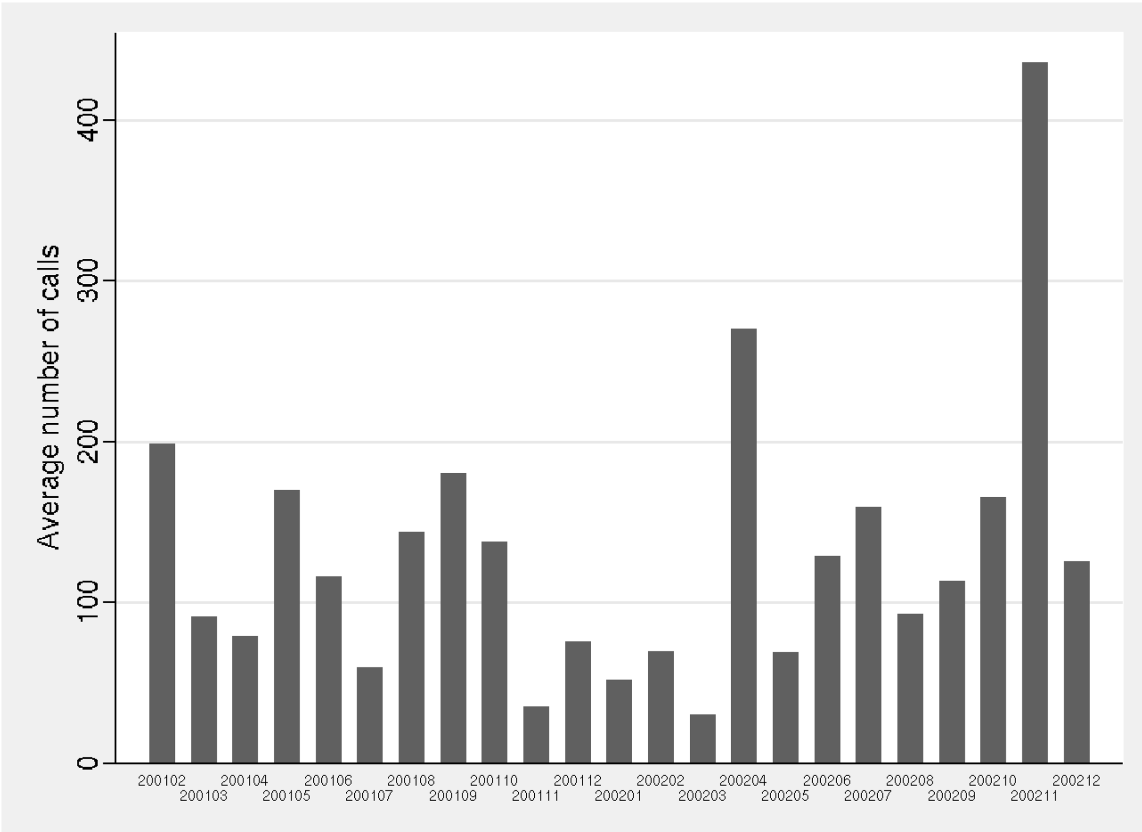


Figure EC.2 Relationship between Number of Calls and Timing of Adoption

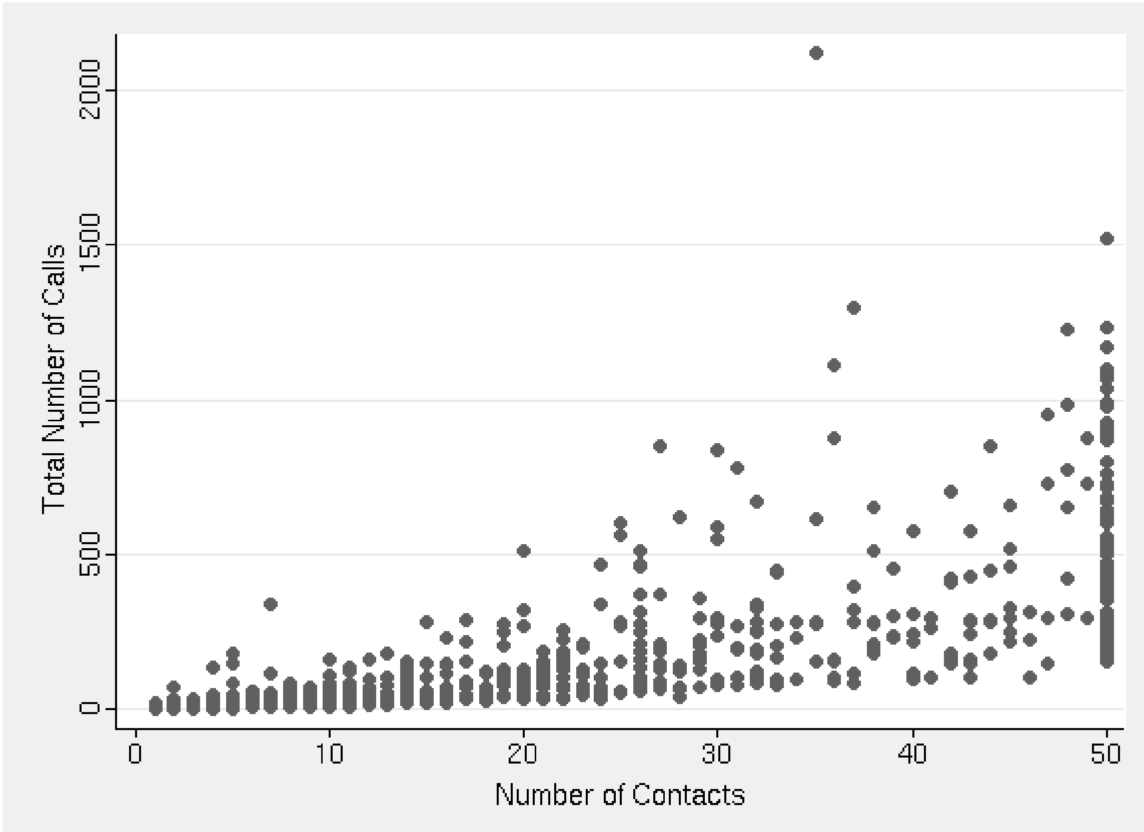


Figure EC.3 Relationship between Number of Calls and Number of Contacts

EC.4. Calculations of Social Network Centrality Measures

All measures of centrality were calculated using the software package UCinet written by Borgatti et al. (2002). Though these measures are very familiar to sociologists, they are unfamiliar to economists. Table EC.4 provides a description of the basic concepts behind the calculation of social network measures. Table 1 provides a technical description of how Borgatti et al. (2002) calculates each of the different measures of centrality.

Table EC.4 Social Network Analysis Terminology

Name	Description
Vertex	A node in a network (in my case, the position the contact occupies in the video-messaging network)
Geodesic	Shortest path between two vertices
Adjacency matrix	A n by n matrix that summarizes whether is a link between any of the n vertices in a network

Table EC.5 How centrality measures are calculated

Name	Description
	Formal Influence
Managerial Status	Indicator variable for whether a contact has a title of Director or higher
	Informal Influence
Betweenness	Proportion of all geodesics linking vertex j and vertex k which pass through vertex i. Formula given by Freeman (1977)
Closeness	The reciprocal of a contact's length of geodesic to every other vertex.
Degrees	The number of vertices adjacent to the given vertex (the contact)
Bonacich Power	$\sum A_{ij}(\alpha+\beta c_j)$, where A is the adjacency, c_j is the centrality of vertex j, and α is a normalization factor. In my specification β=1.
Distance	Distance in km between the employee's city and the contact's city calculated using air travel distances

EC.5. Robustness Checks for Network Measures

As a robustness check I also estimated a linear probability model specification to verify my results. This allowed me (unlike in the Newey two-step methodology) to implement different specifications of the error term such as allowing for robustness. Reassuringly, the results suggest that little changed even when errors were clustered at the regional level.

Table EC.6 Linear Probability Robustness Checks for Base Specification

	Managers			Workers		
	Standard	**Robust**	**Clust.Region**	**Standard**	**Robust**	**Clust.Region**
Installed Worker	0.0003	0.0003	0.0003	0.0022***	0.0022***	0.0022*
	(0.0008)	(0.0009)	(0.0009)	(0.0004)	(0.0005)	(0.0007)
Installed Manager	0.0174***	0.0174***	0.0174*	0.0073***	0.0073**	0.0073**
	(0.0042)	(0.0046)	(0.0063)	(0.0027)	(0.0034)	(0.0015)
TV in employee's region	0.0280*	0.0280*	0.0280**	0.0387***	0.0387***	0.0387*
	(0.0146)	(0.0154)	(0.0086)	(0.0073)	(0.0084)	(0.0151)
Observations	4635	4635	4635	8088	8088	8088

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: Adopters who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the heterogeneity-weighted installed base are the heterogeneity-weighted TV valuation of each employee's manager and worker contacts. TV valuation is measured by the % of prior adopters who watch local TV in that contact's region in the next month.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table EC.7 Linear Probability Model: Reflecting different effects of Centrality

	Managers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0003	0.0014***	0.0074**	0.0010*	-0.0048	-0.0024*
	(0.0009)	(0.0005)	(0.0031)	(0.0005)	(0.0036)	(0.0012)
Installed Manager	0.0174***	0.0030	0.0272**	0.0030	-0.0043	0.0077
	(0.0046)	(0.0024)	(0.0109)	(0.0026)	(0.0053)	(0.0047)
TV in employee's region	0.0280*	0.0299*	0.0287*	0.0317**	0.0530***	0.0436***
	(0.0154)	(0.0154)	(0.0154)	(0.0153)	(0.0152)	(0.0153)
Observations	4635	4635	4635	4635	4635	4635

	Workers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0022***	0.0015***	0.0084***	0.0012***	-0.0016	-0.0024***
	(0.0005)	(0.0004)	(0.0021)	(0.0003)	(0.0025)	(0.0008)
Installed Manager	0.0073**	0.0036*	0.0401**	0.0053**	-0.0039	0.0011
	(0.0034)	(0.0021)	(0.0159)	(0.0023)	(0.0035)	(0.0045)
TV in employee's region	0.0387***	0.0394***	0.0394***	0.0376***	0.0504***	0.0433***
	(0.0084)	(0.0084)	(0.0083)	(0.0084)	(0.0084)	(0.0083)
Observations	8088	8088	8088	8088	8088	8088

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: Adopters who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the heterogeneity-weighted installed base are the heterogeneity-weighted TV valuation of each employee's manager and worker contacts. TV valuation is measured by the % of prior adopters who watch local TV in that contact's region in the next month.

Robust Standard Errors: * p<0.10, ** p<0.05, *** p<0.01

EC.6. Prediction of Networks

I use a linear probability model to obtain estimates of what characteristics affect an adopter's decision to video-message another employee. Table EC.8 summarizes and provides a precise description of the dependent variable and the RHS variables. I use a linear probability model because I have nearly 10,000 right-hand-side variables, and because probit specifications are notoriously bad at handling large numbers of dummy variables. Reassuringly, when I compare the results for a probit specification with a linear probability model for a more restricted number of right-hand-side variables, they produce similar predictions.

Table EC.8 Description of variables used in prediction of contacts

Variable	Description	Mean	Std. Dev.
	LHS Variable		
Link	Indicator Variable for whether employee i and employee j make a video-messaging call from August 2003 to August 2004	0.0045	0.067
	RHS Variables		
26x26 Interaction Dummies between i and j's city location			
64x64 Interaction Dummies between i and j's field of specialization			
4x4 Interaction Dummies between i and j's title			
2x2 Interaction Dummies between i and j's product			
7x7 Interaction Dummies between i and j's geographical product market			
	Total Observations:4,541,161		

EC.7. Robustness Checks for Predicted Measures

Table EC.9 Linear Probability Model: Reflecting effects of centrality for predicted behavior of non-adopters

	Managers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0009	0.0039***	0.0023***	0.0014***	0.0031	-0.0026***
	(0.0013)	(0.0015)	(0.0005)	(0.0003)	(0.0024)	(0.0008)
Installed Manager	0.0027***	-0.0062	-0.0025	-0.0016	0.0019	0.0076***
	(0.0006)	(0.0045)	(0.0016)	(0.0010)	(0.0039)	(0.0016)
TV in employee's region	0.0349***	0.0425***	0.0422***	0.0402***	0.0502***	0.0459***
	(0.0092)	(0.0092)	(0.0091)	(0.0091)	(0.0094)	(0.0092)
Observations	8186	8186	8186	8186	8186	8186

	Workers					
	Regular	**Betweenness**	**Closeness**	**Degrees**	**Power**	**Distance**
Installed Worker	0.0003	0.0009	0.0017***	0.0009***	0.0018	-0.0016***
	(0.0012)	(0.0007)	(0.0003)	(0.0002)	(0.0014)	(0.0004)
Installed Manager	0.0023***	-0.0026	-0.0006	-0.0000	-0.0003	0.0034***
	(0.0003)	(0.0032)	(0.0010)	(0.0006)	(0.0019)	(0.0012)
TV in employee's region	0.0261***	0.0304***	0.0285***	0.0280***	0.0312***	0.0299***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0035)	(0.0035)
Observations	23603	23603	23603	23603	23603	23603

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: All employees who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the heterogeneity-weighted installed base are the heterogeneity-weighted TV valuation of each employee's manager and worker contacts. TV valuation is measured by the % of prior adopters who watch local TV in that contact's region in the next month.

* p<0.10, ** p<0.05, *** p<0.01

Robust Standard Errors

EC.8. Influence of Direct and Indirect Contacts

In my regressions, I focus only on the influence of the adoption decisions of direct contacts. However, theoretically, indirect contacts may matter too if employees place an option value on their being in the network. To test this, I estimated another specification that included both the installed base of direct contacts and the installed base of indirect contacts. The results in Table EC.10 provide empirical evidence that suggests that only direct contacts have a significant impact on adoption decisions.

Table EC.10 Only Direct Contacts Matter

	Managers		Workers	
	Probit	**Probit IV**	**Probit**	**Probit IV**
Installed Worker	0.0044	0.0007	0.0230***	0.0151**
	(0.0064)	(0.0099)	(0.0054)	(0.0065)
Installed Manager	0.1514***	0.0997***	0.0688***	0.0597**
	(0.0196)	(0.0286)	(0.0201)	(0.0276)
Installed Worker 2	0.0015	0.0024	-0.0013	-0.0000
	(0.0021)	(0.0031)	(0.0017)	(0.0025)
Installed Manager 2	-0.0022	-0.0014	0.0005	0.0003
	(0.0024)	(0.0019)	(0.0012)	(0.0017)
TV in employee's region	0.1693*	0.1815*	0.3758***	0.3892***
	(0.0962)	(0.0979)	(0.0790)	(0.0826)
Observations	4520	4520	7933	7933

Dependent Variable: Indicator for when an employee first makes an outward video-messaging call

Sample: Employees who have not yet made a video-messaging call

Dummies for month, region, title, product included in all regressions

Instruments for the different installed base measures are the TV valuation of each employee's direct and indirect manager and worker contacts. TV valuation is measured by the % of prior adopters who watch local TV in that contact's region in the next month. * p<0.10, ** p<0.05, *** p<0.01